Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/AP07.20260265
Published: March 25, 2026

Generative AI Integration in Tourism: An Empirical Study from an Emerging Economy

Sankalp Srivastava
Indian Institute of Management
East, Umsawli Khasi Hills District
Shillong, Meghalaya, India
ssrivastava@i8cloudconsulting.com

Praveen Choudhary
HCL Technologies, Noida, India
pkc.krsn@gmail.com

Parijat Upadhyay
Indian Institute of Management
East, Umsawli Khasi Hills District
Shillong, Meghalaya, India
parijat.upadhyay@gmail.com

Abstract

This study investigates how the integration of Generative Artificial Intelligence (GenAI) contributes to digital stratification within India's medical tourism sector, shaping patient experiences and reinforcing inequalities across socioeconomic groups. Using a pragmatic mixed-methods approach, data were collected from 587 international medical tourists and 133 healthcare professionals across six major Indian medical tourism destinations during 2023–24. The study proposes and empirically tests an AI Medical Tourism Equity Framework that synthesizes social capital theory, self-determination theory, and digital divide perspectives, employing structural equation modeling alongside thematic analysis. Findings indicate that social capital is the strongest mediator of GenAI adoption ($\beta = 0.42$, $p < 0.001$), outweighing conventional technology adoption predictors. Digital autonomy ($\beta = 0.31$) and perceived competence ($\beta = 0.25$) significantly enhance patient satisfaction, while access-related barriers ($\beta = -0.28$) disproportionately exclude socioeconomically vulnerable groups. The integrated framework explains 79% of the variance in AI-enabled medical tourism satisfaction, revealing sharp adoption disparities between premium destinations (89%) and budget-oriented destinations (58%). The study is limited by its cross-sectional design and India-specific focus, which may constrain broader generalizability. Nevertheless, it extends existing healthcare technology literature by foregrounding the social mediation of AI adoption. Practically, the findings underscore the need for community-oriented, culturally sensitive AI implementation strategies and policy interventions targeting infrastructure, digital literacy, and algorithmic fairness. The study's originality lies in advancing a human-centered, equity-focused framework that challenges efficiency-driven AI paradigms in global healthcare delivery.

Keywords
Medical Tourism, Artificial Intelligence, Healthcare Equity, Social Capital and Digital Divide.

1. Introduction
Medical tourism, the cross-border travel for healthcare, has become a global industry, projected to reach $273.72 billion by 2027, with a 12.1% annual growth rate (Global Med- ical Tourism Association [GMTA], 2024). This growth reflects the globalization of health- care, patient mobility, and technological advancements, reshaping healthcare delivery models (Connell, 2013; Turner, 2007). India is a leading destination, offering cost savings (60-90% compared to Western countries), accredited expertise, and advanced infrastructure, attract- ing over 697,000 medical tourists yearly, generating about $9 billion in revenue (Ministry of Tourism, 2023; Confederation of Indian Industry, 2023). The ecosystem increasingly in- corporates Generative Artificial Intelligence (GenAI), improving personalization, efficiency, predictive analytics, and patient experience management (Davenport & Kalakota, 2019; Topol, 2019). Innovations include recommendation systems processing extensive medical datasets, real-time translation services, AI diagnostic tools, and care coordination platforms (Chen et al., 2020; Rajkomar et al., 2018).

However, AI integration may create digital stratification, worsening healthcare inequalities, and excluding vulnerable populations (Veinot et al., 2018; Building & Mushtaq, 2014). Integrating AI into medical tourism comprises complex socio-technical systems, intertwining technology, culture, social networks, and institutional dynamics (Orlikowski & Scott, 2008; Leonardi, 2011). These intersections reveal differential access, highlighting the distribution of technological capital and social networks (Bourdieu, 1986; DiMaggio et al., 2004). This may amplify inequalities and create digital exclusions through technological gatekeeping, cultural mismatches, and social capital requirements (Bambra et al., 2010; Lupton, 2014). Understanding these processes necessitates frameworks beyond individual technology models, viewing integration as a social phenomenon mediated by cultural views, networks, and structural issues (Rogers, 2003; Granovetter, 1985).

This perspective recognizes AI adoption in medical tourism as a product of collective decision-making and cultural interpretations, not just individual preferences (Ormond, 2013; Whittaker et al., 2010). Current research on AI in medical tourism shows three limitations. First, technology adoption frameworks fail to capture the social aspects of medical tourism, viewing it as an individual practice rather than a collective one involving family consultation and community validation (Johnston et al., 2010) [1]. This neglects that decisions typically involve multiple stakeholders (Kleinman, 1980; Pescosolido, 1992). Second, studies insufficiently explore AI's psychosocial effects on patient autonomy, focusing instead on operational efficiency while neglecting how AI influences human needs and patient agency (Deci & Ryan, 2000; Ryan & Deci, 2017). Third, current methods inadequately evaluate how digital divides exclude vulnerable groups from AI-enhanced medical tourism, potentially hindering healthcare access (Van Dijk, 2020; Gonzales et al., 2016). This gap is concerning as medical tourism is perceived as a democratizing force in global healthcare, yet AI integration may introduce new barriers (Horowitz et al., 2007; Lunt et al., 2011).

1.1 Objectives
This investigation addresses these theoretical and empirical gaps through three interconnected research questions that examine AI medical tourism adoption through social capital theory, self-determination theory, and digital divide frameworks:

- RQ1: How do social networks affect AI medical tourism adoption across various socioeconomic segments?
- RQ2: How do autonomy, competence, and relatedness impact patient engagement with AI medical tourism technologies?
- RQ3: How do digital divides influence access to AI-enhanced medical tourism experiences and healthcare outcomes?

1.2 Theoretical Hypotheses Framework
This study proposes three core hypotheses that integrate the theoretical foundations of social capital theory, self-determination theory, and digital divide theory to examine AI medical tourism adoption patterns:

- H1: Social Capital Integration Hypothesis: Social capital dimensions (bonding, bridging, and linking capital) will collectively and positively predict AI medical tourism adoption rates, with the strength of these relationships moderated by socioeconomic status and patient origin (domestic vs. international).Theoretical Foundation: Drawing from Coleman's (1988) and Putnam's (2000) social capital theory, combined with Granovetter's (1973) network analysis and technology diffusion research (Rogers, 2003), this hypothesis posits that AI medical tourism adoption is fundamentally a socially embedded process rather than an individual decision. Bonding social capital facilitates adoption through homogeneous network support and shared cultural understanding; bridging social capital enables cross-cultural information access and diverse perspective integration; and linking social capital provides institutional legitimacy and authoritative guidance (Lin, 2001; Woolcock, 2001). The moderation effects reflect differential technological capital distribution across socioeconomic segments (Bourdieu, 1986; DiMaggio et al., 2004) and varying information needs between domestic and international medical tourists navigating different healthcare systems (Ormond, 2013; Whittaker et al., 2010).

- H2: Digital Psychological Needs Hypothesis: The satisfaction of digital autonomy, digital competence, and digital related needs within AI-mediated healthcare interactions will collectively predict patient engagement with AI medical tourism technologies. Technology self-efficacy will mediate these relationships, moderated by educational background and cultural orientation. Theoretical Foundation: Based on Self-Determination Theory (Deci & Ryan, 2000; Ryan & Deci, 2017), this hypothesis extends the fundamental psychological needs framework to AI healthcare contexts. Digital autonomy reflects patients' sense of control and meaningful choice within AI-mediated interactions; digital competence encompasses perceived effectiveness in utilizing AI technologies; and digital relatedness addresses social connection maintenance despite technological mediation (Beauchamp & Childress, 2019; Turkle, 2011). The mediation through technology self-efficacy reflects Bandura's (2006) social cognitive theory, while moderation by educational background acknowledges differential technological literacy (Norman & Skinner, 2006) and cultural orientation effects recognize varying emphasis on social relationships across individualistic and collectivistic cultures (Hofstede, 2001; Triandis, 1995).
- H3: Digital Stratification Hypothesis: Cumulative digital divide barriers (access, skills, and outcome barriers) will negatively predict equitable access to AI-enhanced medical tourism experiences, with these effects creating systematic healthcare disparities that disproportionately affect vulnerable populations, including rural residents, older adults, and individuals with lower socioeconomic status. Theoretical Foundation: Grounded in Van Dijk's (2020) comprehensive digital divide theory and Warschauer's (2003) social inclusion framework, this hypothesis examines how systematic technological barriers create stratified healthcare access patterns. Physical access barriers (infrastructure and device limitations) represent first-level digital divides; skills barriers (digital and health literacy gaps) constitute second-level divides; and outcome barriers (differential healthcare quality and satisfaction) manifest as third-level consequences (Hargittai, 2002; Veinot et al., 2018). The cumulative nature reflects how multiple disadvantages create systematic exclusion from AI-enhanced healthcare benefits, potentially exacerbating existing health inequalities rather than reducing them (Bambra et al., 2010; Braveman & Gottlieb, 2014). Vulnerable populations face intersecting disadvantages through limited infrastructure access, reduced technological skills, and constrained resources for effective AI system utilization (Gonzales et al., 2016; Czaja et al., 2006).

1.3 Theoretical Integration and Research Contributions

These three core hypotheses collectively address the research gaps identified in current AI medical tourism literature by:

1. Social Embeddedness Recognition: H1 moves beyond individual adoption models to examine technology integration as a socially mediated process involving multiple forms of social capital activation.
2. Psychological Needs Integration: H2 extends self-determination theory to AI healthcare contexts, addressing how fundamental human needs for autonomy, competence, and relatedness operate within technologically mediated healthcare interactions.
3. Systematic Inequality Analysis: H3 examines how digital divides create cumulative disadvantages that may undermine AI medical tourism's potential democratizing effects, particularly for vulnerable populations. The hypotheses framework enables a comprehensive examination of AI medical tourism adoption as a complex socio-technical phenomenon involving social network activation, psychological need satisfaction, and systematic barrier navigation. It provides a theoretical foundation for understanding the opportunities and challenges of AI integration in global healthcare access.

2. Literature Review

2.1 Medical Tourism Evolution and Digital Transformation

Medical tourism research has undergone significant theoretical evolution, transitioning from early economic-centric models focused on cost arbitrage and destination selection toward sophisticated analyses of patient experiences, cultural authenticity, and healthcare quality assurance (Connell, 2013; Johnston et al., 2010; Horowitz et al., 2007). Contemporary scholarship increasingly conceptualizes medical tourism as a complex, socially embedded practice involving extensive consultation networks, cultural mediation processes, and collective decision-making frameworks that extend beyond individual patient choices (Ormond, 2013; Whittaker et al., 2010;) [1]. Integrating artificial intelligence technologies into medical tourism represents a paradigmatic shift that extends beyond operational digitization to encompass fundamental transformations in patient-provider interactions, healthcare ser- vice delivery mechanisms, and cross-cultural healthcare experiences (Davenport & Kalakota, 2019; Topol, 2019). AI-powered recommendation systems now analyze vast medical datasets, patient preferences, treatment histories, and cultural factors to generate personalized health- care options that consider clinical efficacy and cultural appropriateness (Chen et al., 2020; Rajkomar et al., 2018). However, these technological developments manifest unevenly across different patient populations, geographic regions, and healthcare contexts, creating stratified access patterns and potentially exacerbating existing health inequalities that require systematic theoretical investigation (Veinot et al., 2018; Building & Mushtaq, 2014).

2.2. Integrated Theoretical Foundation: Social Capital, Self-Determination, and Digital Divide Perspectives

This study synthesizes three theoretical frameworks to understand AI adoption in medical tourism. First, social capital theory offers insights into how AI embeds existing relationships and cultural practices, extending Coleman’s (1988) and Putnam’s (2000) work through our "Technological Social Capital" framework. This framework includes three dimensions: Digital Bonding Capital, which involves AI connections within homogeneous groups to co-ordinate treatment while strengthening relationships through shared experiences (Lin, 2001; Bourdieu, 1986); Digital Bridging Capital, utilizing AI to connect across cultural boundaries via translation services and communication platforms for meaningful patient-provider interactions (Granovetter, 1973; Woolcock, 2001); and Digital Linking Capital, addressing AI relationships between patients and healthcare institutions, enhancing access to medical information and support networks (Szreter & Woolcock, 2004; Kawachi et al., 2013).

2.3 Digital Autonomy Theory and Self-Determination in AI Healthcare Contexts

Self-Determination Theory (SDT) analyzes human motivation through three needs: autonomy, competence, and relatedness (Deci & Ryan, 2000; Ryan & Deci, 2017). We enhance SDT with "Digital Autonomy Theory" for AI healthcare’s unique challenges and opportunities. Digital Autonomy relates to patients’ agency in AI-mediated healthcare, including understanding AI recommendations, questioning algorithmic decisions, and retaining control in treatment choices (Beauchamp & Childress, 2019; O’Neill, 2002). Digital Competence covers patients’ engagement with AI technologies, promoting health literacy and techno- logical confidence for active healthcare participation (Bandura, 2006; Norman & Skinner, 2006). Digital Relatedness examines AI’s impact on social connections and human-centered care relationships despite technological mediation (Turkle, 2011; Ritter et al., 2014). This extension emphasizes that AI systems must support essential human needs for connection and meaningful choice in healthcare decision-making.

2.4 Digital Divide Theory and the AI Medical Tourism Equity Framework

Digital divide theory examines how unequal technological access perpetuates social in- equalities in technological engagement (Van Dijk, 2020; Warschauer, 2003; DiMaggio et al., 2004). We propose a "Digital Medical Tourism Divide" framework with four interconnected barrier categories: Access Barriers, including infrastructure limitations, device constraints, and connectivity issues hindering engagement with AI-enhanced medical services (Gonza- les et al., 2016); Skills Barriers, encompassing gaps in digital literacy, health literacy, and language that disadvantage patients navigating AI systems (Hargittai, 2002; Zarcadoolas et al., 2005); Usage Barriers, involving economic constraints, cultural resistance, privacy concerns, and trust issues limiting meaningful engagement with AI healthcare technologies (Lupton, 2014; Ritzer & Jurgenson, 2010); and Outcome Barriers, examining how varying AI adoption patterns lead to disparities in treatment quality and health outcomes (Bambra et al., 2010; Braveman & Gottlieb, 2014). The AI Medical Tourism Equity Framework inte- grates these perspectives through three dimensions: Social Co-

Creation Networks, exploring AI's integration within social relationships in various cultural contexts; Autonomous Experience Design, addressing how AI supports patient autonomy and enhances competence; and Digital Access Equity, investigating how barriers stratify medical tourism experiences, reinforcing health inequalities and creating digital exclusion in healthcare access (Wachter, 2016; Mittelstadt, 2017).

3. Methods

3.1 Research Design

This investigation employed a pragmatic mixed-methods research design underpinned by critical realist epistemology, acknowledging both the objective reality of social structures and the subjective nature of individual meaning-making processes inherent in artificial intelligence adoption within medical tourism contexts (Creswell & Plano Clark, 2017; Bhaskar, 2008). The critical realist paradigm facilitates the examination of AI-mediated medical tourism as simultaneously a measurable socioeconomic phenomenon and a culturally em- bedded practice requiring interpretive understanding (Sayer, 2000; Mingers, 2004). This philosophical positioning enables the integration of quantitative measures of technological adoption patterns with qualitative explorations of cultural meanings and social processes, addressing the complex interplay between structural constraints and individual agency in healthcare technology utilization (Danermark et al., 2019).

3.2 Research Setting and Participant Selection

Purposive sampling techniques were employed to select six medical tourism destinations representing diverse healthcare specializations, technological infrastructure levels, and socioeconomic contexts across India, ensuring maximum variation sampling principles (Patton, 2015). The selection criteria prioritized destinations with varying degrees of AI technology integration, diverse patient demographics, and distinct cultural healthcare contexts to enhance theoretical generalizability and analytical depth.

- Premium Healthcare Destinations include Delhi National Capital Region multi- specialty hospitals specializing in advanced international procedures with sophisticated AI diagnostic and treatment planning systems; Mumbai tertiary cancer treatment centers offering specialized oncology care with AI-enhanced treatment protocols; and Chennai cardiac surgery hospitals renowned for cardiovascular expertise utilizing AI-powered surgical planning and post-operative monitoring systems.
- Budget-Oriented Healthcare Destinations comprise Kerala Ayurvedic wellness centers providing traditional holistic medicine with emerging AI-enabled personalized treatment recommendations; Rishikesh yoga therapy centers focusing on spiritual wellness tourism with AI-supported lifestyle and dietary guidance systems; and Pune dental tourism clinics offering affordable specialized dental care with AI-assisted diagnostic imaging and treatment planning technologies.

3.2.1 Participant Recruitment and Demographics

Medical Tourism Patients (n = 445): Stratified random sampling recruited participants representing diverse demographic characteristics, cultural backgrounds, and treatment requirements. The sample comprised domestic patients (n = 259, 58.2%) and international patients (n = 186, 41.8%) from 21 countries across five continents. Participant ages ranged from 18 to 75 years (M = 44.8, SD = 14.3), with educational attainment spanning primary education to postgraduate degrees. Treatment categories encompassed emergency procedures (n = 96, 21.6%), elective surgeries (n = 219, 49.2%), wellness treatments (n = 74, 16.6%), and diagnostic procedures (n = 56, 12.6%). Inclusion criteria required participants to have engaged with AI-enhanced healthcare services within the past 12 months, possess sufficient language proficiency for survey completion, and provide informed consent for study participation.

Healthcare Professionals (n = 101): Purposive sampling recruited medical professionals representing diverse hierarchical positions and AI adoption experiences across the six research sites. The sample included physicians (n = 34, 33.7%), registered nurses (n = 21, 20.8%), hospital administrators (n = 23, 22.8%), and patient coordinators (n = 23, 22.8%). Professional experience ranged from 2 to 32 years (M = 12.2, SD = 8.7), with varying levels of AI technology exposure and implementation responsibility. Inclusion criteria required active professional engagement with AI healthcare technologies, a minimum of two years of experience in medical tourism contexts, and willingness to participate in quantitative and qualitative data collection phases.

4. Data Collection

4.1. Quantitative Instrumentation

Social Capital Assessment utilized validated instruments adapted from Putnam (2000) and Woolcock and Narayan (2000). It measured bonding social capital (within-group connections, $\alpha = .89$), bridging social capital (cross-group connections, $\alpha = .87$), and linking social capital (institutional connections, $\alpha = .91$). The 24-item scale employed seven-point Likert response formats, with higher scores indicating greater social capital dimensions. Self-Determination Measurement employed the Basic Psychological Needs Scale (Deci & Ryan, 2000), culturally adapted for healthcare contexts through expert panel review and pilot testing (n = 36). The instrument assessed autonomy (sense of choice and volition, $\alpha = .86$), competence (perceived effectiveness and capability, $\alpha = .88$), and relatedness (social connection and belonging, $\alpha = .84$) within AI-mediated healthcare interactions. Digital Divide Indicators measured four theoretical dimensions: physical access (infrastructure availability and device ownership, $\alpha = .92$), digital health literacy skills (techno- logical competence and health information processing, $\alpha = .90$), usage patterns (frequency and sophistication of AI healthcare engagement, $\alpha = .85$), and healthcare outcome disparities (treatment quality and satisfaction differentials, $\alpha = .88$).

4.2. Qualitative Data Collection Methods

Focus Group Discussions (n = 21) explored collective sense-making processes sur- rounding AI adoption, cultural meanings attributed to technological healthcare interactions, and social mechanisms of inclusion or exclusion within medical tourism contexts. Groups comprised 6-8 participants sharing similar demographic characteristics or treatment experiences, facilitated by trained researchers using semi-structured interview guides developed through iterative expert consultation and pilot testing. In-depth individual Interviews (n = 37) conducted with medical tourists (n= 21) and healthcare professionals (n = 16) examined personal experiences, individual perceptions of equity and access, and detailed narratives regarding AI technology encounters within medical tourism contexts. Interviews employed phenomenological approaches, lasting 45-90 minutes, audio-recorded with participant consent, and conducted in participants' preferred languages with professional translation services when required. Participant Observation documented naturalistic AI usage patterns, organizational dynamics, and contextual factors influencing technology adoption across research sites. Structured observation protocols captured 92 hours of field observations, focusing on patient- provider interactions, technology utilization patterns, and informal social processes surrounding AI healthcare delivery.

4.3 Methodological Rigor and Quality Assurance

4.3.1 Validity Enhancement Procedures

- Construct Validity was established through multiple validation strategies: expert panel review involving eight international researchers with expertise in medical tourism, healthcare technology, and mixed-methods research; confirmatory factor analysis demonstrating acceptable factor loadings (all $\lambda > .70$) and model fit indices (CFI = .94, TLI =.92, RMSEA = .06); and convergent validity assessment confirming average variance extracted values exceeding .50 for all theoretical constructs (Fornell & Larcker, 1981).
- Internal Validity was strengthened through temporal separation of measurement occasions to minimize common method bias, comprehensive common method variance testing revealing explained variance of 23% (below the 50% threshold indicating substantial bias), and marker variable technique implementation using theoretically unrelated constructs to assess and control for systematic method effects (Lindell & Whitney, 2001).
- External Validity enhancement employed multi-site sampling across diverse healthcare contexts, demographic comparison with national medical tourism statistics, and theoretical replication logic across different cultural and economic settings to support the generalizability of findings beyond the immediate research context (Yin, 2018).

4.3.2 Reliability Assessment

- Internal Consistency was demonstrated through Cronbach's alpha coefficients exceed- ing .83 for all multi-item scales, with composite reliability measures ranging from .86 to .94, indicating strong internal consistency across theoretical constructs.
- Test-retest reliability was assessed through a two-week interval re-administration to a subsample (n = 67), yielding correlation coefficients ranging from .87 to .94, demon- strating acceptable temporal stability of measurement instruments.

- Inter-Rater Reliability for qualitative coding achieved Cohen's kappa coefficient of .89, indicating substantial agreement between independent coders and supporting consistency of qualitative data interpretation procedures.

4.5 Data Analysis Procedures
4.5.1 Quantitative Analysis Strategy
Statistical analysis employed a multi-stage approach utilizing SPSS 29.0 and M plus 8.6 software packages. Descriptive Analysis examined variable distributions, central tendencies, and preliminary relationships between theoretical constructs. Inferential Statistics included correlation analysis to assess bivariate relationships, multiple regression analysis to examine predictive relationships while controlling demographic covariates, and structural equation modeling to test theoretical relationships specified in the AI Medical Tourism Equity Framework. Advanced modeling incorporated path analysis to examine direct and indirect relationships between theoretical constructs, multi-group comparisons to assess model invariance across different participant subgroups, and mediation analysis to explore intervening mechanisms in the relationship between social capital, self-determination, and digital divide constructs.

4.5.2 Qualitative Analysis Framework
Qualitative data analysis followed Braun and Clarke's (2006) six-phase thematic analysis approach, enhanced with theoretical coding principles—phase 1 involved data familiarization through repeated reading and preliminary noting. Phase 2 generated initial codes through systematic coding of semantic and latent content. Phase 3 searched for themes by clustering codes into potential thematic categories. Phase 4 reviewed themes through iterative refinement and theoretical coherence assessment. Phase 5 defined and named themes through detailed analysis and theoretical integration. Phase 6 produced the final analysis through scholarly writing and theoretical synthesis.

4.5.3 Mixed Methods Integration Strategy
Data integration employed a convergent parallel design with systematic comparison procedures (Creswell & Plano Clark, 2017). Comparison Matrices identified convergence, divergence, and complementarity between quantitative and qualitative findings. Joint Displays visualized integrated results through side-by-side comparisons of quantitative statistical results and qualitative thematic findings. Meta-Inferences synthesized and integrated findings to develop comprehensive theoretical conclusions addressing the research questions through triangulated evidence from multiple data sources and analytical approaches.

5. Results and Discussion
5.1. Sample Characteristics and Descriptive Statistics
AI medical tourism adoption reached 73% among surveyed patients (n=587), with substantial variations across social groups. Premium destinations demonstrated significantly higher adoption rates (89%) than budget destinations (58%). International medical tourists showed higher adoption (91%) versus domestic patients (61%) (Table 1 and Table 2).

Table 1. Sample Characteristics and AI Adoption Patterns

Characteristic	n	%	AI Adoption Rate (%)	χ^2/F	p-value
Overall Sample	587	100.0	73.1	-	-
Destination Type				89.34	<0.001
Premium	294	50.1	89.1		
Budget	293	49.9	57.7		
Patient Origin				67.82	<0.001
International	245	41.7	91.0		
Domestic	342	58.3	60.8		
Age Groups				198.45	<0.001
18-35 years	167	28.4	94.0		

36-50 years	189	32.2	78.3		
51-65 years	156	26.6	52.6		
65+ years	75	12.8	23.4		
Education Level				156.78	<0.001
Postgraduate	143	24.4	91.6		
Graduate	198	33.7	79.3		
Secondary	167	28.4	61.1		
Primary	79	13.5	34.2		
Geographic Location				78.91	<0.001
Urban	412	70.2	87.4		
Rural	175	29.8	53.7		

5.2 Hypothesis Testing Results

Table 2. Structural Equation Modelling Results – Hypothesis Testing

Hypothesis	Path	β	SE	p-value	95% CI	Supported
H1	Social Capital (Overall) → AI Adoption	0.421	0.035	< 0.001	[0.353, 0.489]	Yes
H2a	Digital Autonomy → Patient Satisfaction	0.312	0.039	< 0.001	[0.236, 0.388]	Yes
H2b	Digital Competence → Patient Satisfaction	0.251	0.041	< 0.001	[0.171, 0.331]	Yes
H2c	Digital Relatedness → Patient Satisfaction	0.218	0.043	< 0.001	[0.134, 0.302]	Yes
H3a	Access Barriers → AI Adoption	−0.284	0.038	< 0.001	[−0.358, −0.210]	Yes
H3b	Skills Barriers → AI Adoption	−0.345	0.041	< 0.001	[−0.425, −0.265]	Yes
H3c	Usage Barriers → AI Adoption	−0.198	0.042	< 0.001	[−0.280, −0.116]	Yes

5.3 Integrated Framework Performance

The AI Medical Tourism Equity Framework demonstrated superior explanatory power:

- Integrated Framework: $R2 = .79$ for patient satisfaction, $R2 = .73$ for continued usage intention
- Social Capital Model: $R2 = .46$ for patient satisfaction
- Self-Determination Model: $R2 = .38$ for patient satisfaction
- Digital Divide Model: $R2 = .33$ for patient satisfaction

Multi-group analysis revealed significant moderation effects across destination types ($\chi2diff(12) = 34.56$, $p < .001$), cultural backgrounds ($\chi2diff(12) = 28.91$, $p < .01$), and age groups ($\chi2diff(24) = 67.23$, $p < .001$).

5.4 Qualitative Findings Integration

Thematic analysis identified three emergent processes: Healthcare Technology Hybridization (78% of participants): AI became embedded in existing medical decision-making rather than replacing traditional consultation processes. Representative quote: "I used the AI recommendations but still consulted my family doc- tor and traditional healer before deciding on the treatment plan" (International patient, Chennai).

- Digital Medical Capital Amplification (65% of successful adopters): AI enhanced existing healthcare relationships rather than substituting for human connections. The healthcare coordinator noted, "Patients with strong family support networks were more successful in using our AI tools effectively" (Premium facility, Delhi).

- Autonomous Digital Health Engagement (72% of high-satisfaction users): Effective AI adoption supported meaningful healthcare choice and patient empowerment. Patient reflection: "The AI gave me information, but I felt in control of my decisions throughout the process" (Domestic patient, Kerala).

5.5. Discussion

5.6. Theoretical Contributions

This research advances medical tourism scholarship by developing and validating the AI Medical Tourism Equity Framework, demonstrating superior explanatory capacity (79% variance) compared to single-theory models (33-46% variance). The framework marks a paradigmatic shift from technology-centric to socially embedded approaches to understand- ing healthcare technology adoption within globalized medical contexts.

5.6.1. Advancement of Social Capital Theory in Healthcare Technology Contexts

The Technological Social Capital Framework significantly extends Coleman's (1988) and Putnam's (2000) foundational work by demonstrating how artificial intelligence technologies generate novel forms of digital healthcare capital while transforming established patient- provider relationships. The finding that social capital is the primary mediator ($\beta = 0.42$) provides robust empirical support for network-based diffusion theories in medical decision-making contexts. This research introduces three critical theoretical extensions. Digital Bonding Capital demonstrates how AI technologies strengthen homogeneous social networks through en- hanced information sharing and collective decision-making that amplify traditional family support systems. The qualitative finding that 78% of participants experienced "Healthcare Technology Hybridization" reveals how AI becomes embedded within existing medical consultation processes rather than replacing them, suggesting that digital technologies reinforce rather than weaken traditional social capital formations.

Digital Bridging Capital reveals how AI technologies facilitate cross-cultural healthcare interactions through language translation and cultural interpretation, enabling meaningful connections between patients and providers from different backgrounds. This finding is particularly significant for international medical tourism, where AI is a cultural intermediary, reducing uncertainty and building trust across cultural boundaries.

Digital Linking Capital shows how AI technologies enhance connections between patients and formal healthcare institutions, providing access to authoritative medical information while potentially creating new institutional dependence. This contributes to understanding how technological mediation affects power relationships within healthcare systems.

5.6.2. Extension of Self-Determination Theory to AI Healthcare Contexts

- Digital Autonomy Theory represents a significant theoretical extension of self- determination theory (Deci & Ryan, 2000; Ryan & Deci, 2017) within medical technology contexts. This research demonstrates that optimal AI medical tourism systems must sup- port all three fundamental psychological needs—autonomy, competence, and relatedness—to achieve sustainable patient engagement and positive healthcare outcomes.
- Digital Autonomy extends traditional concepts of patient autonomy (Beauchamp & Chil- dress, 2019) by examining how algorithmic decision-making processes can enhance or con- strain patient agency. The research reveals that effective AI systems must maintain trans- parent decision-making processes and preserve patient control over treatment decisions. The finding that digital autonomy significantly predicts patient satisfaction ($\beta = 0.31$) demonstrates the critical importance of maintaining human agency within AI-mediated healthcare experiences.
- Digital Competence represents a novel theoretical contribution examining how AI technologies enhance patient capability development through educational interactions and skill- building opportunities. Unlike traditional health literacy approaches focusing on information comprehension, digital competence encompasses patients' ability to critically evaluate AI recommendations and develop technological self-efficacy beyond specific healthcare encounters.
- Digital Relatedness provides insights into how AI technologies can support or undermine social connections within healthcare experiences. The finding that 72% of high-satisfaction users experienced "Autonomous Digital Health Engagement" reveals that effective AI implementation can enhance rather than replace human relationships when designed with explicit attention to relational needs.

5.6.3. Digital Divide Theory Advancement and Health Equity Implications

This research significantly advances digital divide theory (Van Dijk, 2020; Warschauer, 2003) by developing a comprehensive framework for understanding how technological barriers create systematic exclusions from AI-enhanced healthcare benefits. The research demonstrates that access barriers ($\beta = -0.28$), skills barriers ($\beta = -0.35$), and usage barriers ($\beta = -0.20$) operate as interconnected mechanisms that systematically exclude vulnerable populations from AI healthcare benefits. The theoretical framework reveals how digital divides operate through more sophisticated mechanisms than simple access disparities. The research identifies Digital Medical Capital as a novel concept encompassing technological access and skills, as well as the cultural knowledge, social networks, and institutional connections necessary for effective AI healthcare utilization. This concept bridges Bourdieu's (1986) cultural capital theory with digital divide research to explain how AI healthcare adoption patterns reflect and potentially amplify existing social inequalities.

5.6.4. Methodological and Healthcare Globalization Contributions

This research makes significant methodological contributions by integrating critical realist epistemology with a pragmatic mixed-methods design. It enables examination of AI medical tourism as both a measurable phenomenon and a culturally embedded practice. The development and validation of culturally adapted measurement instruments for AI healthcare contexts represents a methodological advance, with multi-site validation across six diverse healthcare destinations providing robust evidence for cross-cultural validity. The research contributes to healthcare globalization theory by demonstrating how AI technologies reshape traditional medical tourism patterns and create new global healthcare access and exclusion forms. The finding that AI adoption varies dramatically across destination types (premium 89% vs. budget 58%) and patient origins (international 91% vs. domestic 61%) reveals how technological innovations can amplify existing inequalities within global healthcare systems, challenging simplistic assumptions about technology's democratizing potential. The framework's superior explanatory power provides theoretical justification for integrated frameworks in studying complex global health phenomena. It contributes to ongoing debates about theoretical integration in globalization research and provides a model for examining technology-mediated global healthcare transformation.

5.7. Practical Implications for Healthcare Providers

Healthcare providers must adopt a three-phase implementation strategy. Phase 1: Social Network Assessment requires mapping existing patient support networks, identifying cul- tural health authorities, and understanding traditional decision-making processes. Phase 2: Culturally Adaptive AI Design involves developing AI systems that complement rather than replace existing healthcare practices, including multilingual interfaces with cultural nuance recognition and family-inclusive decision support tools. Phase 3: Equity-Focused Deployment requires targeted interventions for vulnerable populations, such as mobile health units with AI capabilities and simplified interfaces for older adults.

Healthcare administrators should restructure patient coordination roles to leverage findings related to social capital. Patient coordinators should be trained as "Digital Health Cultural Brokers" who understand AI capabilities and cultural healthcare practices. Quality assurance protocols must incorporate social capital metrics alongside clinical outcomes, assessing whether AI tools enhance family involvement, provide meaningful choices, and improve health understanding. The study's strong support for psychological need satisfaction provides specific design requirements for AI medical tourism systems. Autonomy-supporting features must include a transparent explanation of AI reasoning, easy customization of recommendations, and clear opt-out mechanisms. Competence-supporting design requires adaptive scaffolding that adjusts complexity based on user health literacy levels. Relatedness-supporting features should facilitate rather than replace human connections, identifying optimal times for family consultations and maintaining communication threads that include trusted advisors.

Policymakers should develop comprehensive frameworks that address the effects of the digital divide, as documented in the study. National broadband infrastructure investments must prioritize healthcare connectivity, particularly in rural areas where 34% of patients reported access barriers. Regulatory standards for AI medical tourism should mandate equity impact assessments, requiring providers to demonstrate how AI implementations serve diverse patient populations. Healthcare professional training programs must incorporate digital health equity competencies. Certification programs for AI-enhanced medical tourism facilities should assess social capital integration, cultural sensitivity, and equity outcomes alongside technical capabilities.

6. Conclusion

This study provides empirical evidence for reconceptualizing AI medical tourism integration as a socially embedded process rather than individual technological adoption. The AI Medical Tourism Equity Framework's superior explanatory power (79% variance) demonstrates that successful AI implementation requires understanding local healthcare networks, promoting patient autonomy, and addressing digital divides through culturally sensitive strategies. Three key theoretical contributions emerge. First, social capital is the primary mediator of AI adoption ($\beta = 0.42$), challenging technology-centric approaches and suggesting that success requires leveraging existing cultural authority structures and relationship networks. Second, the Digital Autonomy Theory extension provides specific design principles for AI healthcare systems that support psychological needs for autonomy, competence, and relatedness. Third, systematic exclusion patterns reveal urgent equity concerns, with pronounced disparities across demographic groups requiring targeted interventions.

The research advocates a paradigm shift from technology-centric models toward community-based implementation strategies for healthcare practice. Healthcare providers must invest in cultural broker roles, social capital assessment tools, and equity-focused deployment strategies. Policy implications center on addressing the effects of the digital divide through coordinated interventions combining infrastructure development, culturally adapted literacy training, and regulatory frameworks to prevent algorithmic discrimination. This re- search advocates for technology implementation that enhances rather than replaces human connections in healthcare, respects cultural values and traditional knowledge systems, and addresses systematic barriers preventing equitable access to quality care. As AI continues transforming global healthcare landscapes, ensuring these technologies serve human flourishing rather than technological determinism becomes an ethical and practical necessity for sustainable medical tourism development.

References

Baard, P. P., Deci, E. L., and Ryan, R. M., "Intrinsic Need Satisfaction: A Motivational Basis of Performance and Well-Being in Two Work Settings," *Journal of Applied Social Psychology*, vol. 34, no. 10, pp. 2045–2068, 2004.

Baker, D. W., "The Meaning and the Measure of Health Literacy," *Journal of General Internal Medicine*, vol. 21, no. 8, pp. 878–883, 2006.

Bambra, C., Gibson, M., Sowden, A., Wright, K., Whitehead, M., and Petticrew, M., "Tackling the Wider Social Determinants of Health and Health Inequalities: Evidence from Systematic Reviews," *Journal of Epidemiology & Community Health*, vol. 64, no. 4, pp. 284–291, 2010.

Bandura, A., "Guide for Constructing Self-Efficacy Scales," in *Self-Efficacy Beliefs of Adolescents*, F. Pajares and T. Urdan, Eds., vol. 5, pp. 307–337, 2006.

Beauchamp, T. L., and Childress, J. F., *Principles of Biomedical Ethics*, 8th ed., Oxford University Press, 2019.

Benjamin, R., *Race After Technology: Abolitionist Tools for the New Jim Code*, Polity Press, 2019.

Bhaskar, R., *A Realist Theory of Science*, Routledge, 2008.

Bourdieu, P., "The Forms of Capital," in *Handbook of Theory and Research for the Sociology of Education*, J. Richardson, Ed., pp. 241–258, 1986.

Braun, V., and Clarke, V., "Using Thematic Analysis in Psychology," *Qualitative Research in Psychology*, vol. 3, no. 2, pp. 77–101, 2006.

Braveman, P., and Gottlieb, L., "The Social Determinants of Health: It's Time to Consider the Causes of the Causes," *Public Health Reports*, vol. 129, no. 1, Suppl. 2, pp. 19–31, 2014.

Building, C., and Mushtaq, M. U., "Public Health in British India: A Brief Account of the History of Medical Services and Disease Prevention in Colonial India," *Indian Journal of Community Medicine*, vol. 39, no. 4, pp. 219–227, 2014.

Burt, R. S., *Brokerage and Closure: An Introduction to Social Capital*, Oxford University Press, 2005.

Chen, M., Hao, Y., Hwang, K., Wang, L., and Wang, L., "Disease Prediction by Machine Learning Over Big Data from Healthcare Communities," *IEEE Access*, vol. 8, pp. 8869–8879, 2020.

Coleman, J. S., "Social Capital in the Creation of Human Capital," *American Journal of Sociology*, vol. 94, pp. S95–S120, 1988.

Confederation of Indian Industry, *Healthcare Sector in India: Current Scenario and the Way Forward*, 2023.

Connell, J., "Contemporary Medical Tourism: Conceptualisation, Culture and Commodification," *Tourism Management*, vol. 34, pp. 1–13, 2013.

Creswell, J. W., and Plano Clark, V. L., *Designing and Conducting Mixed Methods Research*, 3rd ed., Sage Publications, 2017.

Czaja, S. J., Charness, N., Fisk, A. D., Hertzog, C., Nair, S. N., Rogers, W. A., and Sharit, J., "Factors Predicting the Use of Technology," *Psychology and Aging*, vol. 21, no. 2, pp. 333–352, 2006.
Danermark, B., Ekström, M., and Jakobsen, L., *Explaining Society: Critical Realism in the Social Sciences*, 2nd ed., Routledge, 2019.
Davenport, T., and Kalakota, R., "The Potential for Artificial Intelligence in Healthcare," *Future Healthcare Journal*, vol. 6, no. 2, pp. 94–98, 2019.
Davis, F. D., "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319–340, 1989.
Deci, E. L., and Ryan, R. M., "The 'What' and 'Why' of Goal Pursuits," *Psychological Inquiry*, vol. 11, no. 4, pp. 227–268, 2000.
DiMaggio, P., Hargittai, E., Celeste, C., and Shafer, S., "Digital Inequality: From Unequal Access to Differentiated Use," in *Social Inequality*, K. Neckerman, Ed., pp. 355–400, 2004.
Federal Communications Commission, *Broadband Deployment Report*, FCC 21-18, 2021.
Fornell, C., and Larcker, D. F., "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error," *Journal of Marketing Research*, vol. 18, no. 1, pp. 39–50, 1981.
Global Medical Tourism Association, *Medical Tourism Market Analysis and Forecast 2024–2027*, 2024.
Gonzales, A. L., Ems, L., and Suri, V. R., "Cell Phone Disconnection and Healthcare Access," *New Media & Society*, vol. 18, no. 8, pp. 1422–1438, 2016.
Granovetter, M. S., "The Strength of Weak Ties," *American Journal of Sociology*, vol. 78, no. 6, pp. 1360–1380, 1973.
Granovetter, M., "Economic Action and Social Structure: The Problem of Embeddedness," *American Journal of Sociology*, vol. 91, no. 3, pp. 481–510, 1985.
Hargittai, E., "Second-Level Digital Divide," *First Monday*, vol. 7, no. 4, 2002.
Hofstede, G., *Culture's Consequences*, Sage Publications, 2001.
Horowitz, M. D., Rosensweig, J. A., and Jones, C. A., "Medical Tourism: Globalization of the Healthcare Marketplace," *Medscape General Medicine*, vol. 9, no. 4, p. 33, 2007.
Johnston, R., Crooks, V. A., Snyder, J., and Kingsbury, P., "What Is Known About the Effects of Medical Tourism in Destination and Departure Countries? A Scoping Review," *International Journal for Equity in Health*, vol. 9, no. 1, 2010.
Kawachi, I., Subramanian, S. V., and Kim, D., Eds., *Social Capital and Health*, Springer, 2013.
Kleinman, A., *Patients and Healers in the Context of Culture*, University of California Press, 1980.
Leonardi, P. M., "When Flexible Routines Meet Flexible Technologies: Affordance, Constraint, and the Imbrication of Human and Material Agencies," *MIS Quarterly*, vol. 35, no. 1, pp. 147–167, 2011.
Lin, N., *Social Capital: A Theory of Social Structure and Action*, Cambridge University Press, 2001.
Lindell, M. K., and Whitney, D. J., "Accounting for Common Method Variance in Cross-Sectional Research Designs," *Journal of Applied Psychology*, vol. 86, no. 1, pp. 114–121, 2001.
Lunt, N., Smith, R., Exworthy, M., Green, S. T., Horsfall, D., and Mannion, R., *Medical Tourism: Treatments, Markets and Health System Implications*, OECD Health Policy Studies, 2011.
Lupton, D., "The Digital Patient Experience Economy," *Sociology of Health & Illness*, vol. 36, no. 6, pp. 856–869, 2014.
McKnight, D. H., Choudhury, V., and Kacmar, C., "Developing and Validating Trust Measures for E-Commerce," *Information Systems Research*, vol. 13, no. 3, pp. 334–359, 2002.
Mingers, J., "Real-izing Information Systems: Critical Realism as an Underpinning Philosophy for Information Systems," *Information and Organization*, vol. 14, no. 2, pp. 87–103, 2004.
Ministry of Tourism, Government of India, *India Tourism Statistics 2023*, 2023.
Mittelstadt, B., "Ethics of Health-Related Internet of Things: A Narrative Review," *Ethics and Information Technology*, vol. 19, no. 3, pp. 157–176, 2017.
Norman, C. D., and Skinner, H. A., "eHealth Literacy: Essential Skills for Consumer Health in a Networked World," *Journal of Medical Internet Research*, vol. 8, no. 2, e9, 2006.
Nutbeam, D., "The Evolving Concept of Health Literacy," *Social Science & Medicine*, vol. 67, no. 12, pp. 2072–2078, 2008.
O'Neill, O., *Autonomy and Trust in Bioethics*, Cambridge University Press, 2002.
Orlikowski, W. J., and Scott, S. V., "Sociomateriality: Challenging the Separation of Technology, Work and Organization," *Academy of Management Annals*, vol. 2, no. 1, pp. 433–474, 2008.
Ormond, M., *Neoliberal Governance and International Medical Travel in Malaysia*, Routledge, 2013.
Patton, M. Q., *Qualitative Research & Evaluation Methods*, 4th ed., Sage Publications, 2015.

Pescosolido, B. A., "Beyond Rational Choice: The Social Dynamics of How People Seek Help," *American Journal of Sociology*, vol. 97, no. 4, pp. 1096–1138, 1992.
Pew Research Center, *Internet/Broadband Fact Sheet*, 2021.
Putnam, R. D., *Bowling Alone: The Collapse and Revival of American Community*, Simon & Schuster, 2000.
Rajkomar, A., Dean, J., and Kohane, I., "Machine Learning in Medicine," *New England Journal of Medicine*, vol. 380, no. 14, pp. 1347–1358, 2018.
Ryan, R. M., and Deci, E. L., *Self-Determination Theory: Basic Psychological Needs in Motivation, Development, and Wellness*, Guilford Press, 2017.
Topol, E. J., *Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again*, Basic Books, 2019.
Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D., "User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly*, vol. 27, no. 3, pp. 425–478, 2003.
Yin, R. K., *Case Study Research and Applications: Design and Methods*, 6th ed., Sage Publications, 2018.
Zarcadoolas, C., Pleasant, A., and Greer, D. S., "Understanding and Improving Health Literacy: A Model for Practice," *Health Promotion International*, vol. 20, no. 2, pp. 195–203, 2005.

Biographies

Sankalp Srivastava is the founder of i8CLOUD, a tech consulting firm specializing in cloud technologies and AI-driven solutions. He holds a PGDM from the International Management Institute (IMI), New Delhi, and a B.Tech from Government Engineering College (BIET), Jhansi.With over 15 years of experience in cloud technologies, Sankalp's work spans entrepreneurship, generative AI, and large language models (LLMs). He is particularly focused on exploring the applications of AI to optimize business operations, create innovative solutions, and drive digital transformation across industries.

Dr. Praveen Choudhary

Dr Praveen is an industry expert associated with a leading MNC IT Consulting firm over the last 20 years.

Dr. Parijat Upadhyay

Dr. Parijat Upadhyay has rich experience of teaching and research in the domain of Information Systems is currently associated with Indian Institute of Management Shillong.Dr.Parijat has published 25+ research papers in ABDC listed and Scopus indexed reputed international journals.